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The problem studied concerns reducing the dimension of data by mapping it through rectangular matrix transformations before application of signal processing algorithms. Our work addressed applications of this principle in adaptive beamforming, spectral estimation, and detection problems. While dimension reduction often leads to dramatic reductions in the computational burden of the signal processing algorithm, it can also introduce significant asymptotic performance losses if the transformation is not chosen properly. We choose dimension reducing transformations to optimize performance criteria associated with the problem of interest. Our results indicate that dramatic reductions in dimension can be achieved with relatively small asymptotic performance losses using these design procedures. Performance analyses demonstrate that dimension reduction is most profitably used in applications where relatively short data records are available or fast response time is required. In these cases dimension reduction actually improves performance.

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Statement of the Problem Studied

The problem studied concerns reducing the dimension of data by mapping it through rectangular matrix transformations before application of signal processing algorithms. While this often leads to dramatic reductions in the computational burden of the signal processing algorithm, it can also introduce significant performance losses if the transformation is not chosen properly. Our work addressed applications of this principle in adaptive beamforming, spectral estimation, and detection problems. The following specific issues were addressed:

1) modification of signal processing algorithms for application to reduced dimension data,

2) analysis of asymptotic and short data record performance as a function of the dimension reducing transformation,

3) design of optimal dimension reducing transformations,

4) development of efficient implementation structures for reduced dimension signal processing.

Summary of the Most Important Results

As a result of the linear nature of the dimension reducing transformation, modification of signal processing algorithms for the reduced dimension case has proved to be relatively straightforward. This objective has been accomplished in adaptive beamforming [see, e.g., 6], spectral estimation [2, 7, 11, 14], and adaptive detection [8, 15, 18]. We have also obtained reduced dimension signal processing algorithms (yet unpublished) for adaptive FIR and IIR filtering, Volterra series models, and higher order moment estimation.

Our results support the hypothesis that dimension reduction adversely affects asymptotic performance, but enhances short data record performance. Estimates of the statistics of the data, such as the data covariance matrix, are required by all the algorithms studied. The reduced dimension versions require estimates of fewer statistical parameters because of the dimension reduction process. When relatively short data records are used, the estimates of the reduced dimension statistics are of much higher quality than their full dimension counterparts. If large data records are available (the asymptotic case), the quality of estimates is equivalent. Hence, dimension reduction causes an asymptotic performance loss associated with the information that is discarded. However, in the short data record case, the improvement in the quality of the estimates of statistics introduces a performance gain that usually more than offsets any potential loss associated with discarded information. Specific examples include:

1) Partially adaptive beamformers have degraded interference cancellation capability [1, 4, 6, 9, 20] but have improved adaptive convergence rates [3, 6, 16].

2) Reduced dimension minimum variance based spectrum estimates have increased bias, but have smaller variance [7, 11, 14].

3) Reduced dimension generalized likelihood ratio adaptive detectors have improved detection performance (for fixed false alarm rate) with short data records in spite of SNR losses due to dimension reduction; with long data records the SNR losses are the dominant factor and dimension reduction leads to a loss in detection performance [8, 15, 18].

Furthermore, the minimum quantity of data required for existence of a particular signal processing algorithm is generally decreased by the dimension reduction operation. These results indicate that dimension reduction is most profitably used in applications where relatively short data records are available or fast response time is required.

Optimality criteria for designing dimension reducing transformations have been chosen based on the performance analyses described above:

1) For partially adaptive beamforming the goal is to maximize interference cancellation with as few adaptive weights as possible. Since the actual interference scenario is unknown, we maximize interference cancellation over a set of likely scenarios [1, 6, 9, 20].

2) In minimum variance spectrum estimation the goal is to minimize sidelobe leakage or bias using as few degrees of freedom as possible. The true spectrum is unknown, so we minimize bias over a set of likely spectra [7, 11, 14].

3) The goal in the reduced dimension detection problem is to maximize the probability of detection using a small dimension detector. This is equivalent to maximizing SNR. Again, since the actual noise scenario is unknown, we maximize over a likely set of scenarios [8, 15, 18].

These criteria lead to analytically intractable optimization problems, so we have pursued approximate solutions. The partially adaptive beamforming and minimum variance spectrum estimation design problems are very similar. While the detection problem at first seemed quite different, we have shown that it can be reduced to a problem of the same form as the partially adaptive beamforming and minimum variance spectrum estimation problems [8, 15]. Hence, the procedures for obtaining approximate solutions that have been developed for partially adaptive beamforming [1, 6, 9, 20] are applicable to all three cases. Of particular note is the method reported in [9, 20] that approximately finds the smallest transformation subject to a constraint on the worst case asymptotic performance. Simulations indicate that dramatic reductions in dimension can be achieved with relatively small asymptotic performance losses using these design procedures.

A novel cascade decomposition of the generalized sidelobe canceller implementation for partially adaptive beamforming has been developed [5, 17]. This structure has many of the advantages of lattice based adaptive filters. The computational burden associated with determining the adaptive weights is distributed over a series of lower order problems and beamformers with differing numbers of degrees of freedom can be implemented simultaneously and efficiently. In [10] we establish that the cascade structure is analogous to the modified Gram-Schmidt algorithm and show that these structures offer computational efficiencies when simultaneously implementing beamformers based on differing constraint sets.

Another result of note is our recent work on using dimension reduction principles to avoid the signal cancellation that results in adaptive beamforming when there is correlation between signal and interference [19]. The idea is to restrict the degrees of freedom so that the beamformer cannot cancel the signal but remains able to cancel the interference. Our initial results indicate that this approach can be very effective.

We have also investigated use of quadratic constraints for controlling beamformer response [4,12,13] and preventing signal cancellation associated with correlated interference [22]. Quadratic constraints do not implement the "hard" dimension reduction associated with a linear transformation, but rather a soft form. Components of the data are not completely discarded, but are de-emphasized.

Publications

Reviewed Journal Papers and Book Chapters

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2. B. Van Veen and L. Scharf, "Estimation of Structured Covariance Matrices and Multiple Window Spectrum Analysis," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. ASSP-38, pp. 1467-1472, August 1990.

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4. B. Van Veen, "Minimum Variance Beamforming With Soft Response Constraints," *IEEE Transactions on Signal Processing*, vol. 39, pp. 1964-1972, September 1991.

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8. K. Burgess, B. Van Veen, and C. Lee, "Subspace Based Adaptive Detection," *IEEE Transactions on Signal Processing*, submitted.

9. F. Qian and B. Van Veen, "Partially Adaptive Beamformer Design Subject to Worst Case Performance Constraints," *IEEE Transactions on Signal Processing*, submitted.

10. R. Sharma and B. Van Veen, "Modular Structures for Adaptive Beamforming and the Gram-Schmidt Preprocessor," *IEEE Transactions on Signal Processing*, submitted.

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11. M. Rim and B. Van Veen, "Reduced Degree of Freedom Minimum Variance Spectrum Estimation," *Twenty-Third Annual Asilomar Conference on Signals, Systems, and Computers Conference Record*, pp. 619-623, November 1989.

12. B. Van Veen, "Minimum Variance Beamforming with Soft Response Constraints," *Twenty-Third Annual Asilomar Conference on Signals, Systems, and Computers Conference Record*, pp. 43-47, November 1989.

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18. K. Burgess and B. Van Veen, "Improved Adaptive Detection Performance via Subspace Processing," *IEEE 1992 International Conference on Acoustics, Speech, and Signal Processing*, pp.V 353 - V 356, March 1992.

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Participating Scientific Personnel

Barry Van Veen - Principal Investigator

Graduate Students (many of these did not receive direct financial support)

1. Minjoong Rim: received M.S. degree May 1990.
2. Tsung Ching Liu: received Ph.D. degree December 1990.
3. Rajesh Sharma: received M.S. degree December 1992.
4. Qian Feng: expecting Ph.D. degree August 1993.
5. Keith Burgess: expecting Ph.D. degree August 1994.
6. Bruce Williams: withdrew from school for family reasons
7. Chong Lee: withdrew from school because of visa problems